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Unintended consequences of trade in environmental innovation: Agricultural emissions, sectoral leakage, and the Kuznets curve hypothesis

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Abstract: Mitigating emissions from the agricultural sector is crucial for achieving sustainable development goals. However, controlling emissions in one sector can lead to unintended consequences in others through leakage effects. Grounded in the theoretical propositions of sectoral shift theory (SST), the rebound effect, and leakage effects, this study investigates the asymmetric impact of environmentally sound technology (EST) imports and exports on agricultural emissions (N_2O and methane) within the framework of the agricultural Kuznets curve (AKC). Utilising a balanced panel dataset of 105 countries from 2010 to 2020, we employ the Westerlund cointegration test to establish long-run relationships among variables. Method of Moments Quantile Regression (MMQR) estimations reveal a positive effect of EST imports and exports on agricultural N_2O emissions, intensifying the impact at higher quantiles. This suggests that industrial emission reductions through EST may have unintended consequences in agriculture via two mechanisms: emission leakage from industry to agriculture and increased agricultural emissions resulting from productivity improvements through the rebound effect. Nevertheless, in line with SST, our results indicate that sustainable agricultural trade can contribute to mitigating agricultural emissions. The AKC hypothesis holds across almost all models. These findings underscore the importance of developing tailored policies to design EST specifically for the agricultural sector, ensuring more effective emission reductions.

Keywords: Greenhouse gas emissions; environmental technology; quantile regression; rebound effect; carbon leakage; sustainable agriculture

The Glasgow Climate Pact of 2021 calls for a 45% reduction in carbon dioxide (CO_2) emissions by 2030 relative to 2010 levels (Depledge et al. 2022). The pact further emphasises support for developing countries to achieve sustainable growth while aiming to limit global temperature rise to 1.5 °C above pre-industrial levels (van de Ven et al. 2023). However, focusing solely on CO_2 reductions while neglecting other potent greenhouse gases like nitrous oxide (N_2O) and methane (CH_4) may hinder countries' ability to achieve comprehensive sustainability (Filonchyk et al. 2024). N_2O and CH_4, primarily from agricultural sources, have sig-

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nificantly higher global warming potentials than CO_2 (Chataut et al. 2023). N_2O primarily released from fertiliser use and soil management practices, has a global warming potential approximately 298 times that of CO_2 over a 100-year period (Montoya et al. 2021). Methane, largely emitted from livestock and rice paddies, is about 25 times more potent than CO_2 over the same timeframe (Pekkarinen 2020). These gases not only contribute disproportionately to climate change but also persist in the atmosphere for extended periods, with N_2O having a lifetime of about 114 years (Tian et al. 2020). Their potency means that even relatively small emissions can have substantial long-term impacts on global temperature and climate patterns (Magazzino et al. 2023).

While countries pursue various sustainability initiatives including green technological innovations (Li et al. 2024), green finance (Sultanuzzaman et al. 2024), digitalisation (Meiling et al. 2021; Lee et al. 2024a), or energy efficiency (Lee and Yahya 2024), primarily focused on CO_2 emissions, this emphasis may overlook other significant greenhouse gases, particularly from agricultural sources. This imbalanced approach could potentially limit the overall effectiveness of climate mitigation efforts and hinder progress towards comprehensive sustainability. To examine this proposition, we analyse the effect of imports and exports of environmentally sound technologies (EST) on agricultural emissions (N_2O and CH_4).

The hypothesis that trade in EST can primarily increase agricultural emissions can be grounded in three economic concepts. First, the rebound effect, also known as the Jevons paradox, suggests that increased efficiency through environmental innovation may reduce industrial emissions but indirectly encourage expansion of agricultural productivity (Pan et al. 2021; Han and Zhou 2024). Second, the leakage effect posits that emissions reduction in one sector (industry) through green technology can elevate emissions in an alternative sector (agriculture), especially in countries with a comparative advantage in agriculture (Beck et al. 2023). Finally, the sectoral shift theory (SST) explains how economic transition towards more service and technology-oriented structures through green technologies may shift resources and focus away from traditional industrial sectors (Busch and Amarjargal 2022). This shift could inadvertently lead to an intensification of agriculture to maintain economic output, potentially increasing agricultural emissions.

Countries engaged in EST trade primarily focus on reducing industrial CO_2 emissions, with importers pursuing technology adoption and exporters seeking profit generation, while overlooking the significant challenge of agricultural emissions. We test this proposition using the agricultural Kuznets Curve (AKC) framework, as applied by Sharma et al. (2021) and Lee et al. (2024b). The AKC posits an inverted U-shaped relationship between agricultural productivity and agricultural emissions, where initial mechanisation increases emissions until a threshold is reached, after which improved technologies and environmental practices lead to emission reductions.

Our study contributes to the literature in several significant ways. First, it is a pioneering investigation examining the effect of both imports and exports of EST on agricultural emissions. While numerous studies have explored the negative impact of green technology on CO_2 emissions (Habiba et al. 2022; Lin and Ma 2022; Milindi and Inglesi-Lotz 2022; Sharif et al. 2022), the effect on agricultural emissions has been largely overlooked. Drawing on the theoretical propositions of the rebound effect, leakage effect, and SST, we investigate whether agricultural emissions remain unaddressed despite increasing trade in environmental technologies.

Second, we employ the AKC, which has been underexplored in previous research. Most studies have utilised the environmental Kuznets Curve (EKC) when estimating the effect of agriculture on N_2O or CH_4 emissions (Zambrano-Monserrate and Fernandez 2017; Haider et al. 2020; Uddin 2020; Tarazkar et al. 2021; Yahya and Lee 2023a). While the EKC provides a broader perspective on economic development and overall environmental impact (Phuc Nguyen et al. 2020), the AKC offers a more targeted and nuanced understanding of how agricultural practices, technologies, and policies directly influence farming-related emissions.

Third, we estimate the asymmetric effect of EST trade on agricultural emissions, considering two key factors. Countries with higher agricultural emissions may have more industrialised farming practices, where efficiency gains from EST in other sectors could lead to increased resource allocation to agriculture, potentially intensifying production and emissions. Additionally, countries with higher emissions may have more established, emission-intensive agricultural practices that are resistant to change, even as EST is adopted in other sectors. Furthermore, the existence of an AKC varies across the agricultural emissions distribution due to differing levels of development among countries (Czyżewski and Kryszak 2018).

As a robustness check, we employ two unique proxies to estimate the effect of EST trade on agricultural

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emissions. We multiply agricultural imports with EST imports and agricultural exports with EST exports to assess if targeted sectoral EST can mitigate agricultural emissions.

MATERIAL AND METHODS

Sample and measurements

The study's dependent variable is agricultural emissions, primarily comprising two types: nitrous oxide and methane. N_2O emissions result from fertiliser use (both synthetic and animal manure), while CH_4 emissions primarily stem from savanna burning, non-energy waste burning, rice cultivation, animal waste, and livestock. The main explanatory variables are imports and exports of ESTs in current USD, which are technologies that significantly reduce environmental impact compared to conventional alternatives.

To estimate the AKC, we employ agricultural value added [(as a percentage of gross domestic product (GDP)] and its squared term. Control variables include financial development, measured by domestic credit to the private sector by banks (as a percentage of *GDP*), and *GDP per capita*. Financial development can facilitate access to credit and investment in more efficient, sustainable agricultural technologies, potentially reducing farming-related emissions (Wang et al. 2020). Moreover, as *GDP* increases, economies often shift towards more service-oriented sectors and become less agriculture-dependent. This transition, coupled with increased environmental awareness and stricter regulations, can contribute to a reduction in agricultural emissions (Leng et al. 2023). Data on EST is sourced from the Our World in Data (OWID) database, while all other variables are obtained from the World Bank's World Development Indicators (WDI).

Due to data limitations on EST imports and exports, the study covers the period from 2010 to 2020. After balancing the panel, a sample of 105 countries is retained. Among sample countries, China leads EST trade, while Sao Tome and Principe and Comoros record the lowest exports and imports respectively, highlighting significant disparities in environmental technology trade. The complete list of countries is provided in Electronic supplementary material (ESM) Table S1, while Table S2 presents detailed information on the data, including measurements and sources.

Empirical model

Following the theoretical propositions of SST, rebound effect, and leakage effect, we analyse the impact of EST imports and exports on agricultural emissions using the following baseline model:

$$AGEM_{it} = \beta_0 + \beta_1 IEST_{it} + \beta_2 AGVA_{it} + \\ + \beta_3 AGVASQ_{it} + \beta_4 GDP_{it} + \beta_4 FD_{it} + \varepsilon_t \quad (1)$$

where: *AGEM* – agricultural emissions; i.e. N_2O and CH_4; *IEST* – imports and exports of environmentally sound technologies; *AGVA* – agricultural productivity (agricultural value added); *AGVASQ* – squared term to examine AKC; *GDP* – gross domestic product *per capita*; *FD* –financial development.

Statistical techniques

Our empirical strategy begins with comprehensive diagnostic testing, including cross-sectional dependence, slope homogeneity, second-generation panel unit root tests, and Westerlund cointegration analysis (detailed in Exhibit A in ESM). Given the presence of cross-sectional dependence, we employ the Driscoll-Kraay (DK) estimator, which provides standard errors robust to spatial and temporal dependence, offering superior performance over conventional ordinary least square (OLS) estimation (Driscoll and Kraay 1998; Li et al. 2024). The DK estimator can be estimated as follows:

$$\beta^{DK} = (X'X)^{-1} X'Y \quad (2)$$

$$Var(\beta^{DK}) = (X'X)^{-1} \hat{S}^{DK} (X'X)^{-1} \quad (3)$$

where: β^{DK} – Driscoll-Kraay estimator; X – vector of independent variables; Y – dependent variable; $Var(\beta^{DK})$ – variance-covariance matrix of the estimator; $\hat{S}^{DK}$ – DK standard error estimator and can be defined as:

$$\hat{S}^{DK} = \hat{\Omega}_0 + \sum\nolimits^{m}_{k=1} w(k,m)[\hat{\Omega}_k + \hat{\Omega}_k'] \quad (4)$$

where: $\hat{\Omega}_k = T^{-1}\sum\nolimits^{T}_{t=k+1} \hat{h}_t \hat{h}'_{t-k}$, $\hat{h}_t = T^{-1}\sum\nolimits^{N}_{i=1} x_{it}\hat{u}_{it}$, $w(k,m)$ – weight function; m – maximum lag length.

While OLS or DK estimator provide a useful average relationship, they focus on estimating the conditional mean of the dependent variable, which can be limiting in certain scenarios (Lee and Yahya 2024). They may not capture the full picture of how variables interact, especially in datasets with heterogeneous relationships or when dealing with non-normal distributions (Yahya and Lee 2023b). Quantile regression offers several advantages over OLS. It allows for a more comprehensive analysis by estimating relationships at different points of the conditional distribution of the dependent vari-

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able, not just the mean. This is particularly useful when the impact of independent variables varies across the distribution (Canay 2011).

Quantile regression is also more robust to outliers and can handle heteroscedasticity more effectively (Koenker and Bassett Jr 1978). It provides insights into the entire conditional distribution, making it valuable for analysing data with skewed distributions or when interested in extreme values (Waldmann 2018). Additionally, quantile regression does not assume a particular distribution for the error terms, making it more flexible for various types of data (Davino et al. 2013). The basic form of quantile regression can be formulated as follows:

where: x – set of exogenous variables; y – endogenous

$$Quant_{\theta}(y_i | x_i) = x\beta_{\theta} + \mu_{\theta}, 0b\theta b1 \quad (5)$$

variable; μ – error terms in the θ^{th} distribution point of the criterion variable.

We employ Method of Moments Quantile Regression (MMQR) that offers several advantages over conventional quantile regression, making it a more robust and flexible approach for analysing distributional effects (Machado and Silva 2019). Unlike traditional quantile regression, MMQR does not rely on the assumption of independent and identically distributed errors, making it more suitable for complex data structures with potential heteroscedasticity and serial correlation (Ike et al. 2020). This method also offers computational efficiency, especially for large datasets, as it does not require the solution of a complex optimisation problem for each quantile (Anwar et al. 2021). Additionally, MMQR allows for the easy implementation of hypothesis tests and the construction of confidence intervals, facilitating more comprehensive statistical inference (Lee et al. 2023). Accordingly, Equation (1) can be re-estimated as follows:

$$Q_{\tau}(AGEM_{it}) = \alpha_{\tau} + \beta_{1\tau}EST_{it} + \beta_{2\tau}AGVA_{it} + \\ + \beta_{3\tau}AGVASQ_{it} + \beta_{4\tau}GDP_{it} + \beta_{5\tau}FD_{it} + \varepsilon_t \quad (6)$$

RESULTS AND DISCUSSION

Diagnostic tests

Prior to analysis, all variables underwent logarithmic transformation to address potential non-linearity and heteroscedasticity. Table 1 presents the descriptive statistics of the transformed variables, revealing that average agricultural methane emissions slightly exceed N_2O emissions. Furthermore, the data indicate that imports of ESTs surpass exports. The CD test results strongly reject the null hypothesis of cross-sectional independence for all variables. Additionally, the slope homogeneity test provides evidence of significant slope heterogeneity in the model (see Table S3 in ESM). These findings underscore the importance of employing second-generation panel unit root and cointegration tests, which are robust to cross-sectional dependence and slope heterogeneity.

The results of panel unit root test suggest that all variables are stationary at first difference (see Table S4 in ESM) and Westerlund cointegration test reveals long run cointegration between underlying variables (see Table S5 in ESM). Given these findings, we proceed to estimate the long-run coefficients using two complementary approaches: the DK estimator and the MMQR. The DK estimator is chosen for its robustness to cross-sectional dependence and heteroscedasticity,

Table 1. Descriptive statistics and cross-sectional dependence (N = 1 155)

Variables	Mean	SD	Min.	Max.	Skewness	Kurtosis	P = 25	P = 75	CD
AGN_2O	8.091	2.146	1.303	12.788	–0.763	3.917	7.099	9.437	245.008***
AGMETH	8.327	2.361	0.816	13.127	–0.871	4.218	7.083	9.778	245.020***
EEST	19.851	3.204	7.946	26.279	–0.390	3.029	17.487	22.510	244.819***
IEST	21.144	2.151	15.222	25.825	–0.155	2.594	19.622	22.784	245.045***
AGVA	22.086	1.990	16.897	27.754	–0.046	3.002	20.777	23.452	245.062***
GDP	8.876	1.387	5.384	11.725	–0.145	2.294	7.999	9.917	245.027***
FD	3.808	0.737	1.752	5.543	–0.173	2.376	3.283	4.386	244.459***

*** significance at 1% level; SD – standart deviation; CD – cross-sectional dependence test; AGN_2O –agricultural N_2O emissions; *AGMETH* – agricultural methane emission; *EEST* – exports of environmentally sound technologies; *AGVA* – agricultural productivity (agricultural value added); *GDP* – gross domestic product; *FD* – financial development

Source: Compiled and calculated by the authors using data from Our World in Data and World Development Indicator

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while the MMQR allows us to examine the potentially heterogeneous effects across different quantiles of the agricultural emissions distribution.

Driscoll-Kraay estimations

The results obtained from the DK estimator, presented in Table 2, reveal that both exports and imports of EST are associated with increased agricultural N_2O emissions. These findings align with the theoretical underpinnings of the SST, rebound effect, and leakage effect. The observed relationship suggests that exporting countries may prioritise addressing their industrial or CO_2 emissions before selling EST to importing nations, while importing countries may not acquire sufficient EST specifically targeted at mitigating their agricultural N_2O emissions. This finding aligns with the recent work of Abbasi and Zhang (2024), who demonstrated a positive association between green innovation, agricultural land use, and greenhouse gas (GHG) emissions.

Interestingly, our analysis indicates no statistically significant effect of EST trade on agricultural methane emissions. This differential impact on N_2O and methane emissions warrants further investigation and may reflect the varying sources and mitigation strategies for these two greenhouse gases in the agricultural sector. Furthermore, our results provide robust evidence for the existence of an AKC across all models. This finding implies that agricultural productivity initially increases emissions during the scaling stage, but beyond a certain threshold, emissions decrease due to composition and technique effects (Sharma et al. 2021).

Method of Moments Quantile Regression (MMQR)

Although the DK estimator is an effective tool for addressing CD, panel quantile regression is more suitable when variables do not follow a normal distribution. Several normality tests were conducted, indicating that variables are not normally distributed (Table S6 in ESM). Consequently, the MMQR is employed to further elucidate the study's findings. Table 3 presents the results of the MMQR for the first model. Consistent with the theoretical propositions of rebound and leakage effects, our findings indicate that EST exports increase N_2O emissions, with a slightly more pronounced effect

Table 2. Driscoll-Kraay estimations

Variables	(1)	(2)	(3)	(4)
	AGN₂O	*AGN₂O*	*AGMETH*	*AGMETH*
EEST	0.114***	–	–0.006	–
	(0.004)	–	(0.003)	–
IEST	–	0.245***	–	0.014
	–	(0.009)	–	(0.014)
AGVA	2.873***	2.964***	3.624***	3.599***
	(0.041)	(0.039)	(0.059)	(0.060)
AGVASQ	–0.045***	–0.049***	–0.057***	–0.057***
	(0.001)	(0.001)	(0.001)	(0.001)
GDP	–0.165***	–0.219***	–0.157***	–0.174***
	(0.008)	(0.011)	(0.013)	(0.012)
FD	–0.420***	–0.390***	–0.330***	–0.337***
	(0.037)	(0.033)	(0.020)	(0.020)
Constant	–32.458***	–35.073***	–40.691***	–40.476***
	(0.518)	(0.455)	(0.700)	(0.711)
Observations	1 155	1155	1 155	1 155
R-squared	0.876	0.878	0.857	0.857
Number of groups	105	105	105	105

*** significance at 5% level, respectively; *AGN₂O* – agricultural N_2O emissions; *AGMETH* – agricultural methane emission; *EEST* – exports of environmentally sound technologies; *IEST* – imports of environmentally sound technologies; *AGVA* – agricultural productivity (agricultural value added); *AGVASQ* – squared term of agricultural value added; *GDPPC* – groos domestic product; *FD* – financial development

Source: Compiled and calculated by the authors using data from Our World in Data and World Development Indicator

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Table 3. MMQR estimations for the relationship between *EEST* and *AGN_2O*

Variables	Quantiles								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
EEST	0.113***	0.113***	0.113***	0.113***	0.114***	0.114***	0.114***	0.114***	0.115***
	(0.018)	(0.015)	(0.015)	(0.015)	(0.016)	(0.017)	(0.019)	(0.023)	(0.028)
AGVA	3.865***	3.473***	3.333***	3.182***	3.003***	2.762***	2.496***	2.158***	1.740***
	(0.265)	(0.225)	(0.218)	(0.219)	(0.227)	(0.248)	(0.279)	(0.333)	(0.406)
AGVASQ	–0.066***	–0.058***	–0.055***	–0.052***	–0.048***	–0.043***	–0.037***	–0.030***	–0.021**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	yes	yes	yes	yes	yes	yes	yes	yes	yes

, * significance at 5 and 1% level, respectively; N = 1 155; dependent variable is agricultural N_2O emissions; MMQR – Method of Moments Quantile regression; *AGN_2O* – agricultural N_2O emissions; *EEST* – exports of environmentally sound technologies; *AGVA* – agricultural productivity (agricultural value added); *AGVASQ* – squared term of agricultural value added
Source: Compiled and calculated by the authors using data from Our World in Data and World Development Indicator

at higher quantiles. This relationship can be explained through two mechanisms. First, countries with higher N_2O emissions typically have larger agricultural sectors, where efficiency improvements may paradoxically lead to expanded production and higher emissions due to the rebound effect (Hassapoyannes and Blandford 2019; Laborde et al. 2020). Second, the focus on EST exports might create resource allocation challenges.

These findings suggest a potential trade-off between EST export development and domestic environmental management. Countries intensively focused on EST exports may face constraints in allocating sufficient resources, expertise, and policy attention to their domestic agricultural sector's environmental performance (Ogle et al. 2023). This resource allocation challenge can lead to reduced implementation of sustainable agricultural practices, particularly in countries where institutional capacity is limited (Paul et al. 2023). Furthermore, the results provide strong evidence for the existence of the AKC across all nine quantiles examined, indicating a consistent non-linear relationship between agricultural productivity and agricultural emissions across different levels of N_2O output (Sharma et al. 2021).

Table 4. MMQR estimations for the relationship between *IEST* and *AGN_2O*

Variables	Quantiles								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
IEST	0.182***	0.204***	0.214***	0.225***	0.238***	0.253***	0.269***	0.290***	0.319***
	(0.039)	(0.034)	(0.033)	(0.033)	(0.034)	(0.037)	(0.041)	(0.048)	(0.060)
AGVA	4.205***	3.780***	3.573***	3.355***	3.104***	2.818***	2.500***	2.069***	1.495***
	(0.293)	(0.242)	(0.234)	(0.234)	(0.242)	(0.260)	(0.291)	(0.346)	(0.430)
AGVASQ	–0.075***	–0.066***	–0.062***	–0.057***	–0.052***	–0.046***	–0.039***	–0.030***	–0.018*
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	yes	yes	yes	yes	yes	yes	yes	yes	yes

*, *** significance at 10 and 1% level, respectively; N = 1 155; dependent variable is agricultural N_2O emissions; MMQR – Method of Moments Quantile regression; *IEST* – imports of environmentally sound technologies; *AGN_2O* – agricultural N_2O emissions; *AGVA* – agricultural productivity (agricultural value added); *AGVASQ* – squared term of agricultural value added
Source: Compiled and calculated by the authors using data from Our World in Data and World Development Indicator

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Table 4 presents the results of the second model using MMQR. Similar to the effects observed with EST exports, the imports of EST are also positively and significantly associated with agricultural N_2O emissions across all nine quantiles examined. This suggests that importing countries may prioritise EST that addresses industrial and CO_2 emissions, potentially neglecting technologies specifically targeted at mitigating other GHGs such as agricultural N_2O emissions (Duxbury and Mosier 2022; Foong et al. 2022). Additionally, the adoption of new technologies often precipitates a rebound effect, whereby increased efficiency leads to expanded production rather than reduced emissions (Laborde et al. 2020; Khatri-Chhetri et al. 2023). In the agricultural context, this phenomenon could manifest as farmers utilising more efficient irrigation or fertiliser application systems to cultivate larger areas or intensify production, ultimately resulting in elevated overall N_2O emissions (Mamun et al. 2021; Du et al. 2023).

The analysis reveals a notable disparity in the impact of EST trade on different agricultural greenhouse gases. While the effects of EST imports and exports are statistically significant for N_2O emissions, Tables 5–6 indicate no significant impact on agricultural CH_4 emissions across any of the examined quantiles. This finding suggests that methane emissions, primarily from livestock management and rice cultivation, remain largely unaffected by EST trade. This discrepancy can be attributed to several factors. Firstly, the rebound effect appears more pronounced for N_2O-related activities. The improvements in fertiliser efficiency might lead to expanded cultivation, thereby increasing N_2O emissions. In contrast, methane-producing activities such as livestock rearing are less likely to expand proportionally with technological advancements (Zhen et al. 2023). Furthermore, this pattern may reflect a potential bias in EST development and trade towards technologies addressing soil and crop management practices, which primarily affect N_2O emissions, rather than those targeting livestock and rice cultivation methods that influence methane production.

Robustness checks

In line with the proposition that the sector-specific approach is more effective in mitigating emissions, we developed measures for sustainable agricultural imports (AGSEXP) and exports (AGSIMP) to assess their potential in reducing agricultural emissions. The results, presented in Table S7 in ESM, indicate that sustainable agricultural exports significantly mitigate N_2O emissions, with the effect being more pronounced at higher quantiles. Similarly, Table S8 in ESM, demonstrates that sustainable agricultural imports mitigate N_2O emissions across all quantiles examined.

Regarding the impact of *AGSEXP* and *AGSIMP* on methane emissions, the results show some variation (see Tables S9 and S10 in ESM). This suggests that sustainable agricultural trade becomes increasingly effective in mitigating agro emissions as emission levels surpass certain thresholds. Consistent with sectoral shift theory, our findings indicate that both imports and exports of EST specifically targeting the agricultural sector are effective tools in addressing agricultural emissions. This evidence is partially sup-

Table 5. MMQR estimations for the relationship between *EEST* and *AGMETH*

Variables	Quantiles								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
EEST	–0.008	–0.007	–0.007	–0.006	–0.006	–0.005	–0.005	–0.004	–0.003
	(0.029)	(0.024)	(0.022)	(0.021)	(0.020)	(0.021)	(0.021)	(0.024)	(0.030)
AGVA	5.113***	4.531***	4.249***	3.900***	3.627***	3.368***	3.119***	2.737***	2.046***
	(0.427)	(0.347)	(0.321)	(0.302)	(0.294)	(0.298)	(0.313)	(0.350)	(0.445)
AGVASQ	–0.089***	–0.076***	–0.071***	–0.063***	–0.058***	–0.052***	–0.047***	–0.039***	–0.024**
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)	(0.010)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	yes	yes	yes	yes	yes	yes	yes	yes	yes

, * significance at 5, and 1% level, respectively; N = 1 155; dependent variable is agricultural CH_4 emissions; MMQR – Method of Moments Quantile regression; *EEST* – exports of environmentally sound technologies; *AGMETH* – agricultural methane emission; *AGVA* – agricultural productivity (agricultural value added); *AGVASQ* – squared term of agricultural value added

Source: Compiled and calculated by the authors using data from Our World in Data and World Development Indicator

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Table 6. MMQR estimations for the relationship between *IEST* and *AGMETH*

Variables	Quantiles								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
IEST	–0.077	–0.045	–0.027	–0.003	0.013	0.030	0.045	0.070	0.119*
	(0.062)	(0.053)	(0.049)	(0.045)	(0.045)	(0.045)	(0.047)	(0.052)	(0.067)
AGVA	5.062***	4.548***	4.259***	3.879***	3.615***	3.355***	3.101***	2.704***	1.913***
	(0.427)	(0.357)	(0.331)	(0.309)	(0.301)	(0.304)	(0.318)	(0.355)	(0.465)
AGVASQ	–0.086***	–0.076***	–0.070***	–0.063***	–0.058***	–0.052***	–0.047***	–0.039***	–0.024**
	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.010)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	yes	yes	yes	yes	yes	yes	yes	yes	yes

*, **, *** significance at 10, 5, and 1% level, respectively; N = 1 155; dependent variable is agricultural CH_4 emissions; MMQR – Method of Moments Quantile regression; *IEST* – imports of environmentally sound technologies; *AGMETH* – agricultural methane emission; *AGVA* – agricultural productivity (agricultural value added); *AGVASQ* – squared term of agricultural value added

Source: Compiled and calculated by the authors using data from Our World in Data and World Development Indicator

ported by Marcus and Nwaeze (2024), who found that efficient resource allocation toward the agricultural sector can reduce its emissions. This underscores the importance of tailored approaches in environmental technology trade and implementation for achieving significant emission reductions in agriculture.

CONCLUSION

Policy implications

This study examines how EST trade influences agricultural emissions through the AKC framework, analysing panel data from 105 countries (2010–2020). Our findings, robust across DK and MMQR estimations, reveal that both EST imports and exports paradoxically increase agricultural N_2O emissions, with effects varying across emission quantiles. The results confirm the AKC hypothesis, showing that agricultural emissions initially rise with productivity before declining beyond a threshold, driven by technique and composition effects through advanced farming practices.

Our analysis yields three key policy implications. First, the current EST development and trade framework requires reorientation to specifically target agricultural emissions. While existing ESTs effectively address industrial CO_2 emissions, their impact on agricultural N_2O and CH_4 emissions is limited or potentially counterproductive. Second, policymakers should develop sector-specific emissions reduction strategies that account for the unique characteristics of agricultural emissions, particularly focusing on precision agriculture and improved fertiliser management techniques. Third, countries need to strengthen the integration between their industrial and agricultural environmental policies to prevent cross-sectoral emissions leakage, ensuring that emission reduction in one sector does not lead to increases in another.

These findings underscore the need for a differentiated approach to environmental technology development and implementation. Future EST policies should prioritise technologies specifically designed for agricultural emission reduction, supported by comprehensive life-cycle assessments and tailored to regional agricultural practices. Such targeted interventions, would be more effective in addressing agricultural emissions while maintaining productive efficiency.

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